Operational Health Monitoring of Bridges Using Bayesian Model Updating and Computer Vision Techniques

NILOOFAR MALEKGHAINI, HAMED EBRAHIMIAN,
FARID GHAHARI, VINAYAK SACHIDANANDAM,
MATTHEW BOWERS and ERTUGRUL TACIROGLU

ABSTRACT

This study presents a new framework for operational health monitoring of bridges using computer vision and finite element (FE) model updating techniques. In this framework, the bridge acceleration responses and vehicle tracking data are obtained under operational conditions using accelerometers, regular traffic cameras and computer vision techniques. These data are synchronized and integrated with the initial FE model of the bridge through a FE model updating process to jointly estimate the dynamic load of tracked vehicles on the bridge and the unknown FE model parameters. The final estimates of FE model parameters reveal information regarding the location and extent of potential damage in the monitored bridge. This framework is first successfully verified in a numerically simulated environment and then validated using a real-world bridge subjected to traffic excitation due to passage of tri-axle dump trucks.

INTRODUCTION

The growing number of aged in-service bridges necessitates development of new technologies for operational health monitoring of these structures [1]. The available sensing solutions, including non-destructive evaluation and vibration-based monitoring techniques, have important limiting challenges including but not limited to traffic interruption, technology capability, implementation cost, ease of use, etc. To overcome these limitations, this study extends the application of time-domain finite element (FE) model updating to develop a new damage identification framework for bridges under operational conditions. In this framework, the bridge is instrumented with wireless accelerometers and traffic cameras. The traffic, including class and location of vehicles, is classified and tracked using computer vision techniques. Synchronized traffic and accelerometer data, along with the initial FE model of the bridge, are the inputs to the Bayesian FE model updating process to jointly estimate the dynamic vehicular loads and the FE model parameters. The updated FE model is then interrogated to localize and quantify damage in the bridge. The proposed framework is schematically shown in Figure 1.

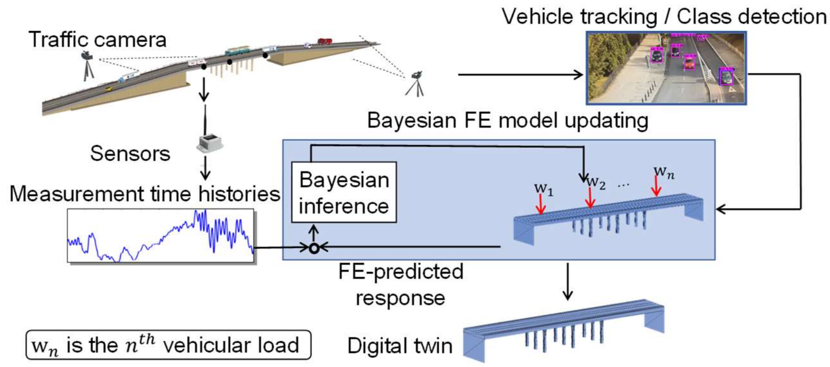


Figure 1. The overall view of the framework.

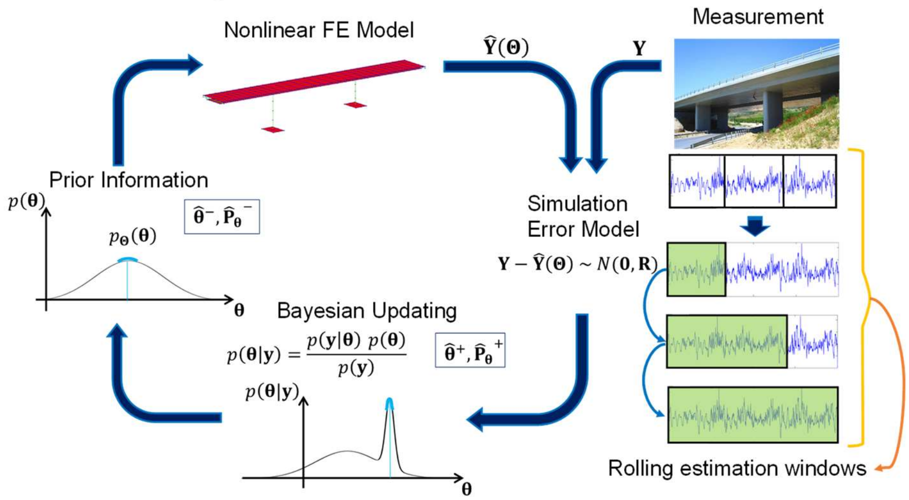


Figure 2. Bayesian model updating process.

BAYESIAN FINITE ELEMENT MODEL UPDATING

The Bayesian FE model updating method is schematically shown in Figure 2 [2,3]. In this process, the unknown model parameters as well as the load of moving vehicles are treated as random variables ($\boldsymbol{\theta}$). The uncertainties of these parameters are characterized by a joint probability density function (PDF) denoted as $\boldsymbol{p}(\boldsymbol{\theta})$, with the mean and the covariance vector/matrix of $\widehat{\boldsymbol{\theta}}$ and $\widehat{\mathbf{P}}_{\boldsymbol{\theta}}$. Using the Bayes rule, the prior estimates of the mean and covariance vector/matrix ($\widehat{\boldsymbol{\theta}}^-$, $\widehat{\mathbf{P}}_{\boldsymbol{\theta}}^-$) are updated to obtain their posterior estimates ($\widehat{\boldsymbol{\theta}}^+$,$\widehat{\mathbf{P}}_{\boldsymbol{\theta}}^+$) and minimize the discrepancy between the measured responses ($\mathbf{Y}$) and the FE model-predicted responses ($\widehat{\mathbf{Y}}(\boldsymbol{\theta})$). In this study, a rolling estimation method is employed in which the time domain is divided into n_s windows, while the $\boldsymbol{s^{th}}$ window is defined between time step $t_0 = 1$ and t_s ($t_s < t_{s+1}$). The above process is iterated at each estimation window until convergence of unknown parameters. Then, the estimation window rolls out in time and the process is repeated using the new batch of data. It is noteworthy that in this specific problem, the size of the unknown parameter vector vary as vehicles with various speeds can enter and exit the bridge at any time. Rolling estimation method is a new approach specifically designed and formulated to address this problem.

VERIFICATION STUDY

This verification study is focused on preliminary design and implementation of the proposed framework using numerically simulated data. For this purpose, a mechanics-based nonlinear FE model of a pre-stressed box girder bridge is developed in OpenSees. Five regions are defined along the length of bridge, and the identifiable damage-related model parameters (here concrete compressive strength and prestressing force) and location of vertical measurement channels are determined using an information-theoretic approach (see Figure 3) [4]. In total, ten different scenarios, including minor localized to severe distributed concrete delamination, reinforcement corrosion, concrete degradation, and tendon corrosion damage scenarios, are considered. For the sake of brevity, only one scenario is presented in detail.

In the presented damage scenario, prestressing force is reduced by 25%, 15%, 15%, 15% and 25% from its nominal value in region 1 to 5 of the bridge (see Figure 4(a) and (b)). A random traffic of 20 seconds, including 14 vehicles in total, is generated on the bridge and the bridge acceleration responses are collected at the 5 selected locations. The collected accelerometers are polluted with artificial zero-mean Gaussian noises to result in the measured responses. The framework of Figure 1 is implemented to jointly estimate the damage-related unknown model parameters and load of vehicles. The final estimates of unknown model parameters are used to infer the damage state of the bridge. The identified damage state of the bridge is shown in Figure 4(c), and it is found to be identical to the true damage state. In addition to the correct estimation of location and severity of damage, the vehicular loads are estimated with a maximum of 1% error.

In all the 10 studied scenarios, damage states at bridge regions are estimated accurately in 86% of regions and with minor errors (maximum of 5%) in regions with incorrect damage estimations. Conservatively, no damage in any of the five regions is underestimated. The vehicular loads are estimated with less than 1% error. TABLE 1 shows a comparison between true and estimated damage states in different damage scenarios. The results demonstrate the efficiency of the proposed framework in damage identification of bridges using numerically simulated environment. In the next section, the performance of the proposed framework is validated in field environment.

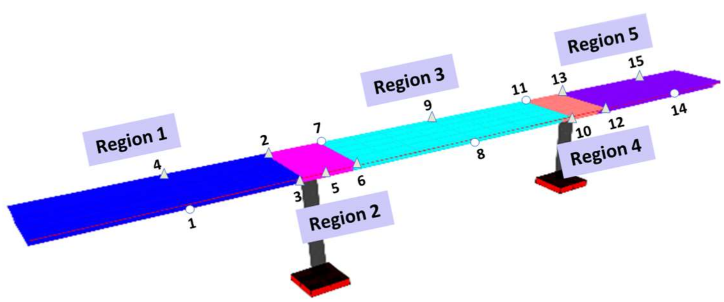
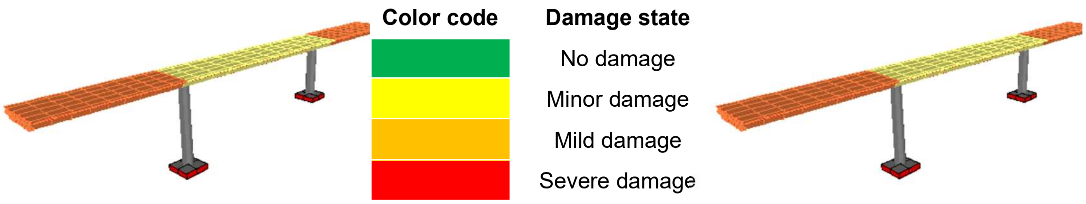


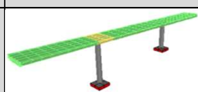
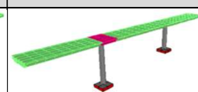
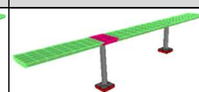
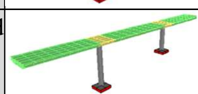
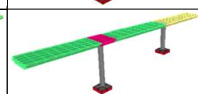
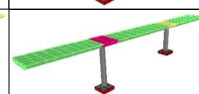
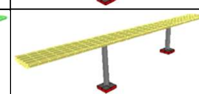
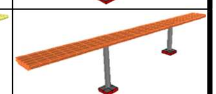
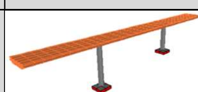
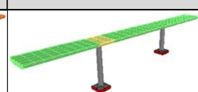
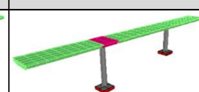
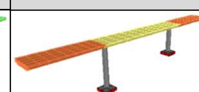
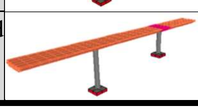
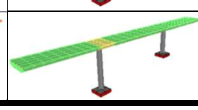
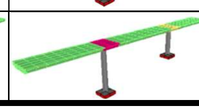
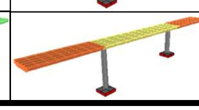
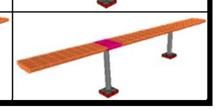
Figure 3. Five regions of bridge and measurement channels. Markers represent the measurement channels used in the identifiability assessment. The circular markers are selected channels for model updating.



(a) (b) (c)

Figure 4. Verification study: (a) True damage state, (b) Color code, and (c) Estimated damage state.

TABLE 1. COMPARISON BETWEEN TRUE AND ESTIMATED DAMAGE STATES. THE COLOR CODES MATCH WITH Figure 4.

Damage scenario #	1	2	3	4	5
True damage state					
Estimated damage state					
Damage scenario #	6	7	8	9	10
True damage state					
Estimated damage state					

VALIDATION STUDIES

The validation study includes the application of the proposed framework in real-world settings. After the successful development of the technology prototype, the proposed framework is performed on an actual decommissioned bridge (east Yutan bridge), for which non-destructive test data – ground penetrating radar (GPR) – is available. The bridge is a steel girder bridge, which was constructed in 1960 and decommissioned from highway service in 2005. The bridge is 122m long (four spans of 30.5m long), 9.8m wide and consists of four 1.37-m-deep welded plate girders with varying flange width over the bridge length. More details can be found in [5].

Traffic of loaded tri-axial dump trucks with average weight of 226kN were used in this study. Vehicles passed the bridge in 60 different traffic scenarios and varying speed between 8 to $90\frac{\text{km}}{\text{hr}}$. Six traffic cameras were installed on temporary tripod supports placed on the roadway shoulder such that the fields of view provided continuous coverage over the bridge. Vertical dynamic response of the bridge was collected from 25 locations using wireless accelerometers. The components of field experiment are shown in Figure 5.

(a) (b) (c) (d)

Figure 5. Field experiment: (a) Bridge view and North direction, (b) An installed wireless accelerometer, (c) A tri-axial dump truck, and (d) Installed traffic cameras.

Data Processing

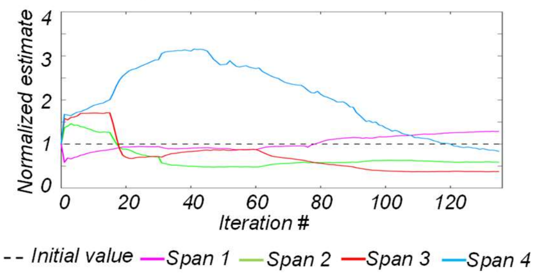
As mentioned earlier, the initial FE model of the bridge and the synchronized tracked traffic and accelerometer data are the input to the Bayesian FE model updating process. To provide the input, the initial linear FE model is developed using the available as-built drawings. Using deep learning methods, the trace of wheel locations is determined for each camera. To associate a given vehicle across multiple camera views, fixed landmarks are used to determine a perspective transformation in UTM coordinates. Then, the tracked locations in UTM coordinate is transformed to the bridge FE model coordinate system. Synchronization between the trace of wheels and accelerations are performed via incorporation of a GPS clock to each of these two systems.

Damage Identification

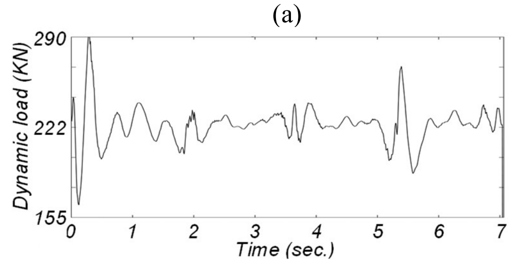
In this step, using model updating process, the initial FE model of the bridge is updated and the dynamic load of traffic – accounting for road roughness and bridge-vehicle interaction – is estimated. Although various test scenarios and cross validations are carried out, for the sake of brevity, only the results for the test scenario with single passage of a 230kN truck with speed of 90km/hr are presented. As mentioned earlier, the bridge initial FE model is developed using the as-built drawings and assuming ideal boundary conditions (fully fixed/free connection in each degree of freedom). However, this assumption is easily violated for such a deteriorated bridge. To reduce the effects of modeling error, arising from the boundary conditions, and to improve the numerical stability and convergence of the model parameters, a two-step FE model updating process is proposed [2]. In the first step, traditional modal-based model updating is used to estimate the model parameters mainly related to the stiffness of boundary conditions and an effective concrete modulus of elasticity for the entire length of the bridge. In the second step, a Bayesian time-domain model updating is carried out using data collected in operational conditions to refine damage estimation by identifying effective concrete modulus of elasticity for each span of the bridge.

The modal-based model updating results show a decrease ($\sim$14%) in concrete modulus of elasticity with respect to its nominal value, which was expected as the bridge is extensively damaged. The updated model, obtained from modal-based model updating, is used as the prior FE model in Bayesian time-domain model updating. Figure 6(a) shows the updating process of effective concrete modulus of elasticity for each span. Spans 1 and 4 are the east and west approaching spans, and spans 2 and 3 are the east and west middle spans, respectively. Final estimates for this parameter in spans 2 and 3 show severe reduction in comparison to the nominal value (58% in average). Moreover, the final estimates of this parameter in span 3 are smaller than span 2, which indicates that span 3 is more deteriorated than span 2. This observation confirms the results of

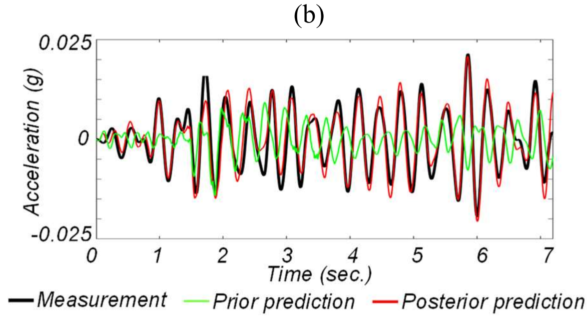
GPR. The concrete modulus of elasticity in spans 1 and 4 are not well-converged as identifiability of these parameters are small due to the presence of pin and hanger connections in the approaching spans. Figure 6(b) presents the estimation of dynamic load of the truck. This figure clearly confirms the dynamic effect of truck load on the bridge due to surface roughness and the interaction between bridge and vehicle. Figure 6(c) compares the measurement with the prior and posterior estimations at the channel with highest amplitude. As it can be seen, there is a reasonable improvement/agreement between the measurements and posterior predictions.



(a)



(b)



(c)

Figure 6. Model updating results: (a) Updating process for effective concrete modulus of elasticity, (b) Dynamic load estimation, and (c) Comparison between measurement, prior and posterior estimations.

CONCLUSIONS

This study proposed a bridge damage identification framework by integrating finite element model updating process with traditional structure monitoring sensors supplemented with non-contact computer vision techniques to track vehicles. Through a two-step finite element model updating process, the material parameters of bridge are estimated and used to assess the location and extent of damage. The first part of this study focused on verifying the proposed framework using numerically simulated data. In the second part, the proposed framework was implemented and validated using real-world data.

REFERENCES

[1] E. Simoen, B. Moaveni, J.P. Conte, G. Lombaert, Uncertainty quantification in the assessment of progressive damage in a 7-story full-scale building slice, J. Eng. Mech. 139 (2013) 1818–1830. https://doi.org/10.1061/(asce)em.1943-7889.0000610.

[2] N. Malekghaini, F. Ghahari, H. Ebrahimian, M. Bowers, E. Ahlberg, E. Taciroglu, A Two-Step FE Model Updating Approach for System and Damage Identification of Prestressed Bridge Girders, Buildings. 13 (2023). https://doi.org/10.3390/buildings13020420.

[3] F. Ghahari, N. Malekghaini, H. Ebrahimian, E. Taciroglu, Bridge digital twinning using an output-only Bayesian model updating method and recorded seismic measurements, Sensors. 22 (2022) 1278. https://doi.org/https://doi.org/10.3390/s22031278.

[4] H. Ebrahimian, R. Astroza, J.P. Conte, R.R. Bitmead, Information-theoretic approach for identifiability assessment of nonlinear structural finite-element models, J. Eng. Mech. 145 (2019) 1–14. https://doi.org/10.1061/(ASCE)EM.1943-7889.0001590.

[5] NOBL, (2023). https://engineering.unl.edu/outdoorbridgelab/.